Personalized Music Recommendation Based on Style Type

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(Full Paper)

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ABSTRACT

As Internet industry constantly develops and the computer penetration rate continues to grow, the number of online music platforms and music users has been able to increase year by year. With that comes more music choices, information overload has become a very prominent problem. Therefore, how to make users choose their favorite music more conveniently is one of the most challenging problems faced by online music recommendation systems. This paper bases on the existing recommendation system research and uses the collaborative filtering algorithm, proposes a music recommendation method from three perspectives: user attributes, music types and time migration. It is found that the online music recommendation from these three perspectives has a good effect, which can provide a reference for the construction of the current online music recommendation system and is also helpful to platform management practice.

Keywords: Online music, information overload, user attributes, music type, time migration.

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INTRODUCTION

With the continuous growth of network users and the development of the digital economy, digital consumption has gradually become the norm for household consumption. In the digital economy, digital music consumption accounts for a large part, and people's daily entertainment is increasingly inseparable from digital music, hence the online music market continues to flourish. As the number of music platforms and music continues to increase, users have a wider range of choices and more freedom to choose, which makes the audiences of online music continue to rise. However, as the scale of original music continuously expands, and the number and types of music are growing rapidly, users need to spend a lot of time and energy to find their favorite music. As a result, users' browsing costs rise dramatically. While looking for favorite music, people often browse a lot of irrelevant music information, and in this process, users are prone to encounter the problem of information overload (Bawden, Holtham & Courtney, 1999). An improperly designed platform recommendation system will cause continuous loss of users. Based on the above background, various recommendation methods have begun to be used on music platforms.

In practical applications, the mainstream music platforms now make recommendations based on a single recommendation method. For example, Shrimps Music uses content-based recommendations and Last.fm music station uses system-based filtering recommendations. The accuracy and coverage of these two types of recommendation methods are difficult to guarantee, at the same time, the recommendation effect is often difficult to meet the real needs of users. Indeed, the characteristics of users, the type of music and the time factor in it should be considered in the recommendation process. However, on the current music platform, joint recommendation from the three aspects has not yet been practiced. This study hopes to try a new recommendation method, based on user attributes, music types and time migration to conduct joint recommendation experiments, and hopes to effectively improve the accuracy and coverage of online music platform recommendations in this way.

RESEARCH REVIEW

Traditionally, recommendation systems (RS) are used by e-commerce websites or platforms to provide users with the products and information they need or are interested in, to assist users in making decisions about which products and services to purchase, and to simulate the process of purchasing by salespeople (Pual *et al.*, 1997). The traditional recommendation system consists of three main modules, namely user information, product information and recommendation algorithm. First, user information is collected, then it is matched with product information using recommendation methods, and relevant recommendation methods are used to filter and match users with their favorite music products and information. Currently, there are three main recommendation methods: content-based recommendation, which extracts the main information and most important features of existing products, including the features that users like and dislike, and uses this part of the features and information to match the user's interests and preferences in the modeling, so that it can recommend products and information with a high degree of matching to the user, thus calculating the similarity between music and users in this method (Riyahi & Sohrabi, 2020) is extremely critical. Collaborative filtering recommendation is one of the most widely used and mature recommendation technology in the current major e-commerce platform, which generally uses KNN (K-NearestNeighbor, KNN) technology. Collaborative filtering recommendation method is through the user's product scores, so as to deduce the user's favorite, and then look for its most similar users. In this process, we look at the products that users similar to him like or buy, and then recommend the corresponding products to the user. The key step is to calculate the similarity between users by calculating cosine similarity (Cheng & Bu, 2020); the recommendation based on association rules mainly considers the rules governing the relationship between users and products, the already purchased products are used as rule headers in the recommendation system, and the recommended objects are the rule body in the recommendation system. By calculating the association rules between different users and different products (Kautz, Selman & Shah, 1997; Wang *et al.*, 2020), we can recommend appropriate products to users, the most classic case is Wal-Mart "beer and diapers", which is widely used in the marketing and management industry. In recommendations based on social network analysis, a social network is a network of relationships formed when people and organizations exchange information, and users often form interrelationships between products and users when they purchase products or browse information on e-commerce web pages, thus forming a social network relationship, through which it is possible to better analyze the correlation between platform users and platform products, and make recommendations based on this correlation (Chen *et al*., 2019). The mixed recommendation has received extensive attention. Because now many recommend methods have their own limitations, such as content-based recommendations often face the problem of cold start, collaborative filtering recommendation methods are often faced with data sparsity and other issues, so we can combine the advantages of various recommendation methods. The mixed recommendation method is a method that combines the strengths and weaknesses of various recommendation methods after considering the advantages and disadvantages of the existing recommendation methods. At present, the most widely used hybrid recommendation in recommendation systems is to combine the collaborative filtering method and the content-based recommendation method (Basu *et al.*, 1998; Pazzani, 1999; Manogaran, Baratharajan & Priyan, 2018; Logesh & Subramaniyaswamy, 2019). For example, Collective Intelligence Social Tagging System (CIST) combines a content-based recommendation approach with a social tagging function based on crowd-sourcing, which makes a significant difference in content-based recommendation system to enrich the item profile and provide more accurate suggestions (Sharma & Kale, 2018; Wang & Sharma, 2018).

Currently, the mainstream music recommendation methods include personalized music recommendation systems based on acoustic metadata (i.e., audio signal analysis), personalized music recommendation systems based on editorial metadata (i.e., expert recommendations), and personalized music recommendation systems based on cultural metadata (i.e., user subjective feelings). Acoustic metadata-based recommendation methods are mainly based on extracting the characteristics of the songs themselves, and such recommendation methods are mainly used in older music recommendation systems, such as audio fingerprinting (Dazhi, 2020), audio acoustic characteristics (Yuan, 2018), and music signals (Gilda *et al.*, 2017). Recommendation systems based on editorial metadata are also known as expert-based recommendation systems, and here experts mainly refer to the singer, lyricist and composer of the song, and this recommendation method is mainly based on collaborative filtering, for example, the famous MoodLogic recommendation system (Celma, 2008) recommends by extracting features and relevant information of the music title, and Celma recommends by using information such as lyrics making recommendations (Celma, 2008). A music recommendation system based on cultural metadata is mainly considered to collect and calculate the subjective feelings of users, which are mainly derived from user reviews, the emotions of the music itself and the genre labels of the music. For example, Knees (2004) make recommendations by classifying artists, Kaji, Hirata and Nagao (2005) calculate similarities by the actions and feedback emotions of users while listening to music. Schedl and Hauger (2012) improved the recommendation algorithm by collecting information such as comments on microblogs and other social media platforms. Francois (2005) provides a detailed summary discussion of different recommendation methods, which is summarized in Table 1.

Table 1: Summary comparison of recommended approaches

Recommended category	Data source	Technology and theory	Recommended advantages	Recommended disadvantages	Typical websites
Content-based online music recommendation	The audio characteristic of the music itself	Word frequency mining and Gaussian mixture models, etc.	Overcoming cold start problems	Low novelty of results	Shrimps music
Collaborative filtering of online music recommendations	User ratings	KNN, NB	Higher novelty	Data sparsity and cold start	Last.fm Music station (Shardanand & Maes, 2012)
Music recommendations based on association rules	Number of comments and retweets shared	Cluster, NB etc.	Personalized recommendation results	Large amount of data to process	Douban Radio Station

Online music recommendations based on social networks	Nodes of Music and Nodes of Users	Random walk model	High accuracy	The structure is more complex	Graph-based MMRF(Lee, 2012)
Hybrid Online Music Recommendations	Combined application of various recommendation methods	DFE	A combination of the above benefits		7HCCMR (Yoshii *et al.*, 2006)

Recommendation systems are currently developing fast and are mostly used in the e-commerce field. Other fields, such as news, movies, music and so on, are now using recommendation systems, but they are developing more slowly and are not as complete as the recommendation systems in the e-commerce field due to the lack of data support in the e-commerce field. Most of the existing music recommendation systems are based on acoustic metadata, editorial metadata, and cultural metadata, and these recommendation systems also have more or less different problems. For example, music recommendation systems based on acoustic metadata cannot represent the music well due to the characteristics of each frame of the music, and therefore the recommendation results cannot really satisfy the users; music recommendation systems based on editorial metadata take the information of experts into account too much, which leads to excessive human costs; music recommendation systems based on cultural metadata need a lot of user feedback information to reach a more accurate recommendation effect. Therefore, this study has theoretical and practical significance to research the personalized music recommendation system from the perspective of music genre, user attributes and time migration.

THEORETICAL BACKGROUND AND MODEL

Theoretical Background and Model

Based on the previous analysis, we will explain and introduce the algorithm and recommended metrics that will be used in this study. Currently, collaborative filtering is mainly carried out by Top-N algorithm, so this study will mainly use this algorithm for the calculation. The sparse linear recommendation algorithm (SLIM) in Top-N can be used to build user matrices through Model-based and predict similarity through Neighborhood-based calculation. In this study, the similarity matrix is built and then similarity calculation is performed to generate the recommendation using KKN. The following section introduces the music genre rating optimization algorithm as well as the recommendation metrics that will be used in the experiment.

Construction of the Similarity Matrix

In every experiment of recommendation system, the recommendation method is the central key, and this experiment uses a combination of user similarity and the type of song to calculate the recommendation. The first step is the construction of a matrix, which is built with the purpose of exploring users' ratings of songs they listened to at different times, so that it is possible to see if their preferences change over time migration. The matrix is decomposed by formula (1).

$$R_{m*n} \approx P_{m*k} * Q_{k*n} = \hat{R}_{m*n} \qquad (1)$$

Definition:

P_{m*n}: represents the relationship between m users and k songs.

Q_{m*n}: represents the relationship between k songs and n users.

The matrix decomposition structure is shown in Figure 1.

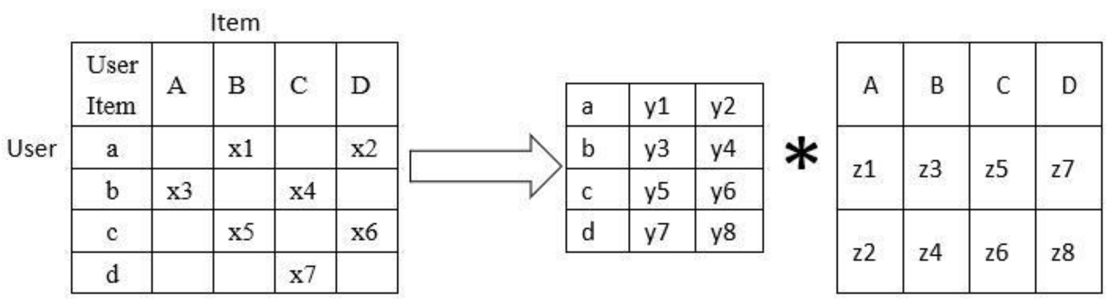

Figure 1: Matrix decomposition

Similarity Calculations

According to the previously established similarity matrix to calculate the user similarity, using the cosine angle formula to calculate the similarity between the user now and previously listened to the song list, by calculating the user ratings on their own at different times to listen to the song, so that the recommendation can be considered from the perspective of both user attributes and time migration, the main use of as formula (2).

$$w_{u,v} = \frac{|N_u \cap N_v|}{\sqrt{|N_u|\ |N_v|}} \tag{2}$$

Definition:
u: represents the song u.
v: represents the song v.
N_u: represents how much the song u is liked by the user.
N_v: represents how much the song v is liked by the user.

Recommendations Generated by KNN

Secondly, the K Nearest Neighbor algorithm is used to train the recommendation model. Since this experiment is based on the score of the Item to make predictions, the K Nearest Neighbor algorithm (KNN) is chosen in this study to train the recommendation model.
The KNN algorithm, commonly called K nearest neighbor algorithm, is used to generate recommendations by calculating the similarity of the nearest K users to the target user, as in formula (3).

$$d(u,v) = \sqrt{\sum_{k=1}^{n} |u_k - v_k|} \tag{3}$$

Definition:
d: represents the spatial distance between two users.
u_k: represents the K neighbors of user u.
v_k: represents the K neighbors of user v.

Score Optimization Algorithm for Music Genres

This study focuses on making recommendations based on music genres, and the most direct basis for recommendations is the user's rating of the music (Xiang, 2012) Therefore, this experiment focuses on the users' liking for that music genre. Currently, the most dominant music genres on NetEase music platform are shown in Table 2.

Table 2: NetEase cloud music style

Main Category	Subcategories
Language	Chinese, European and American, Japanese, Korean, Cantonese, Small languages
Style	Pop, Rock, Folk, Electronic, Dance, Rap, Light Music, Jazz, Country, R&B/Soul, Classical, Ethnic, British, Metal, Punk, Blues, Reggae, World Music, Latin, Alternative/Indie, New Age, Ancient, Post-rock, Bossa Nova
Scene	Morning, evening, study, work, lunch break, afternoon tea, subway, driving, sports, travel, walking, bar
Emotion	Nostalgic, fresh, romantic, sexy, sentimental, healing, relaxing, lonely, emotional, excited, happy, quiet, nostalgi
Theme	Soundtrack, ACG, Children, Campus, Game, Post 70s, Post 80s, Post 90s, Internet Song, KTV, Classical, Cover, Guitar, Piano, Instrumental, List of Names, Post 00s

Source: Top song list categories are style, theme, emotion, scene, and language, and the data used in this study mainly considers "style".

Based on the ranking of the amount of data available, this study mainly selected pop, rock, folk, rap, electronic, light, R&B, classical, and jazz music, each of which has one to three style types for users to choose. The style type is used to evaluate the user's preference for the song, and the formula (4) is used to calculate the user's rating of the music style type.

$$r_{ui} = \sum_b \frac{T_{uib} S_{ub}}{S_u} \tag{4}$$

Definition:
b: represnets the type of music style.
T_uib: is a boolean data of type b for whether user u has selected a style type for music i or not.
S_ub: represents the total number of music styles b for user u.
S_u: represents the total number of all style types selected by user u.
α: is a correction factor.

Recommended Indicators
The main metrics for evaluating a recommendation system are accuracy, recall, coverage and novelty. Because of the low cost of goods shelves on the Internet, it is possible to sell goods at lower prices than offline on many e-commerce sites(Su *et al.*, 2018). At the same time, with the continuous development of the Internet and computers and the changing needs of users, many new evaluation metrics have emerged in the field of recommendation systems. For example, the evaluation index of accuracy is a kind of measurement index suitable for offline experiments, which is a more common metric that measures the predictive ability of recommendation systems.

The common accuracy evaluation mainly includes Top-N prediction method and score prediction. Wherein, Top-N is the first N items to determine whether users are satisfied with the recommendation system to generate recommendations, while score measurement mainly uses accuracy, coverage and novelty (Celma, 2010), diversity (Deldjoo *et al.*, 2016), surprise (Abbas & Niu, 2019), root mean square error (RMSE) (Patro *et al.*, 2020), and mean absolute error (MAE) to determine whether users will be Recommended content gives a higher rating, as shown in formula (5) and (6).

$$\text{Precision} = \frac{\sum_{u \in U} |R_{(u)} \cap T_{(u)}|}{\sum_{u \in U} |R_{(u)}|} \tag{5}$$

$$\text{Recall} = \frac{\sum_{u \in U} |R_{(u)} \cap T_{(u)}|}{\sum_{u \in U} |T_{(u)}|} \tag{6}$$

Definition:
R(u): list of recommendations made on the training set.
T(u): list of recommendations made on the test set.

In this study, we take advantage of the special surprise library of the Python recommendation system, and use the KNN collaborative filtering algorithm in the surprise library function to model the existing data and make similar song list predictions based on the calculations.

EXPERIMENTAL FRAMEWORK AND RESULTS

This study considers the recommendation system construction from three perspectives: user attributes, song type and time migration. The data is collected by crawler, pre-processed including data cleaning, and then undergoes six experimental steps including offline experiments such as user attribute modeling, establishment of similar matrix in collaborative filtering, style scoring, index testing, KNN nearest neighbor algorithm, and index testing to finally generate recommendation results.

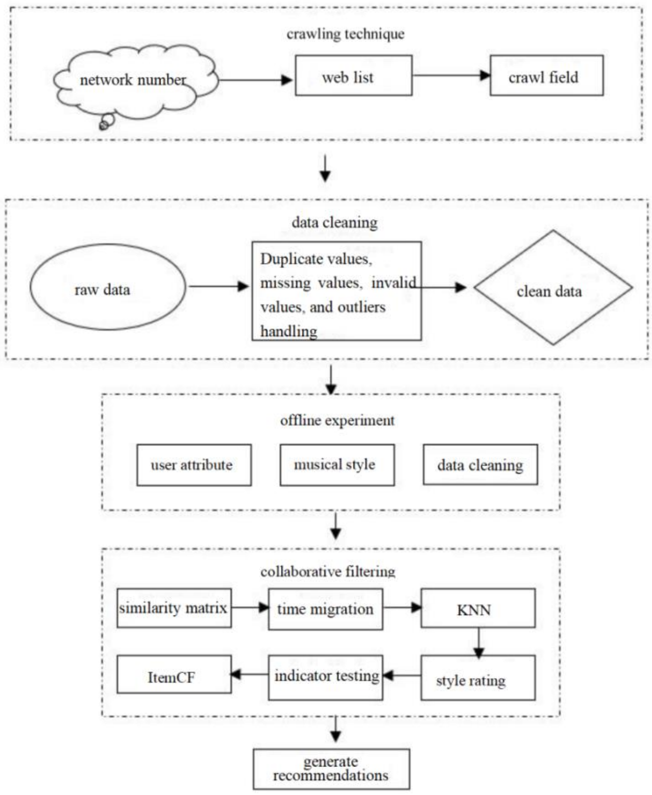

Figure 2: Technology road map

Data Acquisition and Pre-processing

The data in this study is mainly from the NetEase cloud music platform, which has a larger number of listeners and more complete song information. A crawler program written in Python was used to crawl 66291 data information from NetEase cloud music platform. The main fields of data crawled in this study are song list id, music genre of the song list, number of times the song is played, artist, song release time, song duration and other song related field fields.

The data in this study still needs to be in the recommended system format, so in order to facilitate the participation in the calculation and adapt to the needs of the current Python surprise library and the most mainstream recommended system framework, the data format is processed into the most basic format of the library, movielens dataset. The processed data are shown in Figure 4.

Website	id	01_kind	02_kind	create_time	favorite_count	share_count	comment_count	play_count	playlist_count
http://mus	375661355	Subject	After 90	2016/5/5	378664	8285	5243	22238996	178
http://mus	378324005	Language	Chinese	2016/5/9	439451	6161	1441	21703896	210
http://mus	554473977	Subject	List	2017/1/1	283964	2592	2955	20803614	100
http://mus	498708023	Language	Chinese	2016/10/30	464891	6006	2561	20403924	200
http://mus	440561933	Language	Europe and America	2016/8/10	546976	6139	2650	20364706	100
http://mus	758106745	Emotion	Nostalgia	2017/6/10	203546	1171	959	19682608	300
http://mus	497639728	Language	Video Soundtrack	2016/10/29	262802	1485	718	19142126	50
http://mus	375779419	Subject	Excitement	2016/5/5	500907	18925	3743	18364244	59
http://mus	331398396	Emotion	Nostalgia	2016/4/6	500601	5323	1921	17436642	92
http://mus	417794815	Emotion	Chinese	2016/7/8	239929	2131	995	17351472	101
http://mus	330634870	Language	Europe and America	2016/4/5	475196	3379	2642	17258234	181
http://mus	504347934	Language	Chinese	2016/11/7	462340	3291	1241	17223906	53
http://mus	374012053	Language	Europe and America	2016/5/2	267265	1901	1060	16401452	104
http://mus	427850291	Style	Rock and Roll	2016/7/22	478410	3533	2861	16243550	55
http://mus	818563810	Scene	Evening	2017/7/21	337444	11287	22277	15164669	41
http://mus	171664498	Style	Electronic	2016/2/18	683050	13507	3216	15085841	76
http://mus	153864251	Style	Electronic	2016/1/14	313006	2957	1646	14168671	344
http://mus	308905952	Subject	Video Soundtrack	2016/2/28	394877	4910	2209	14157364	100
http://mus	399723525	Language	Europe and America	2016/6/12	433802	6576	2366	14107973	67
http://mus	458329079	Language	Europe and America	2016/9/5	393350	2902	1276	14090920	15
http://mus	517438933	Emotion	Sentimental	2016/11/23	348668	3017	829	13973394	78
http://mus	698720887	Language	Europe and America	2017/4/16	178391	866	517	13914202	101
http://mus	367649303	Emotion	Alone	2016/4/22	341332	2477	1888	13870706	117
http://mus	307592533	Language	Europe and America	2016/2/25	191853	1886	2091	13323389	44
http://mus	449559997	Style	World Music	2016/8/23	354523	3601	2423	13312312	76

Figure 3: Examples of partial data shots

The Id represents the id value of the song list; kind represents the style type of the song list, which is used for the later style rating calculation; create_time, which represents the creation time, is used for the later time migration calculation; and the data in the latter column are the number of collections, number of shares, number of comments, number of plays and number of songs, which will be used in the further research in the future.

Modeling

The online music recommendation system is similar to the traditional recommendation system model, which mainly consists of three parts: user information module, music resource model, i.e., recommendation object modeling, and personalized music recommendation algorithm, as shown in Figure 8.

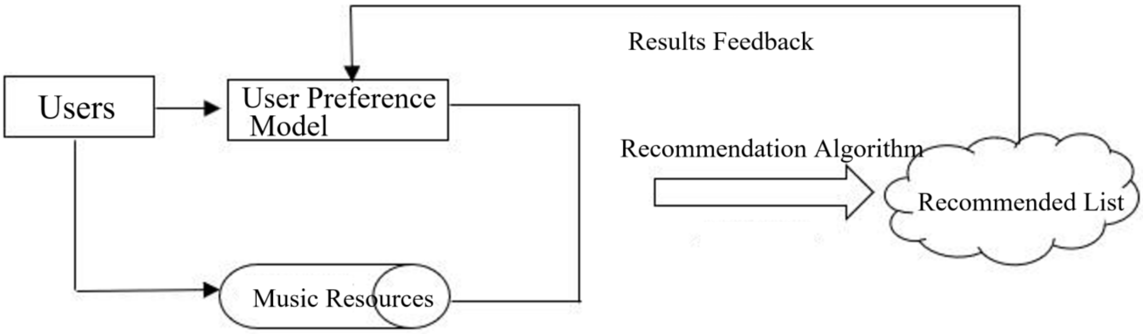

Figure 4: Modeling

The focus of this research experiment is on the music resource module, which mainly contains some information about the song list: song list ID, number of songs, singer and music style and so on, and the recommendation is mainly based on the music style information in it.

At the same time, we can see from the previous three methods that content-based recommendations have less available data in the music domain, and at the same time, they are difficult to implement and difficult to discover new user preferences, so the novelty of recommendations is relatively small; recommendations based on association rules consider fewer objects and have a lower coverage rate; music recommendations based on social networks have a large computation volume and a complex structure, and often require cross-platform integration of data. Therefore, each of the three methods has its own advantages and disadvantages.

The collaborative filtering recommendation algorithm used in this study can well avoid the disadvantages of the above three methods through user attributes, style types and time migration perspectives, and at the same time the computation volume is relatively small, which is used in all major music platforms at present.

Experimental Setup

There are three main common experimental methods used in the recommended system, including User Study, Offline Experiment and Online experiment. In this study, the experimental method is mainly an offline experiment. In this study, the existing dataset is divided into two datasets according to the data length of 8:2, the former is the Training Set and the latter is the Test Set.

Collaborative filtering recommendation algorithm mainly includes two kinds, one is the user-based collaborative filtering algorithm UseCF, the other is the product-based collaborative filtering algorithm and ItemCF, in the beginning of the experiment using a small portion of data to compare the two algorithms, this study takes K = 10, the results are shown in Table 3.

Table 3: UserCF and ItemCF

	UserCF	ItemCF
Recall	0.41348	0.43487
Precision	0.37293	0.40143
Popularity	3.45781	3.27159
Coverage	0.51246	0.53841

According to the data in the above table, the indicators of user-based collaborative filtering algorithm, i.e., UserCF, including Recall, Precision, Popularity and Coverage are lower than product-based collaborative filtering algorithm, i.e., ItemCF, so the product-based collaborative filtering algorithm is used in this study.

In this study, in order to find the most appropriate K value, the ItemCF was taken for K=5,10,20,30 respectively, and the specific results are shown in Table 4.

Table 4: ItemCF at different K values

K	5	10	20	30
Recall	0.30142	0.32157	0.45841	0.39281
Precision	0.27364	0.31921	0.38805	0.35421
Popularity	3.10323	3.11451	3.14276	3.15834
Coverage	0.51348	0.51967	0.50124	0.49523

According to the results of the above table, it can be seen that as the value of K increases, the recall and accuracy rates appear to increase and then decrease. The highest recall and accuracy rates are 0.45841 and 0.38805 when K is taken as 20, which can be determined that the algorithm is more accurate when K = 20 in this study.

In this study, the song types are classified first and then the user ratings of different types of songs are calculated for recommendation, but in order to study the effect of different K values, so the UserCF is then calculated separately when K=5,10,20,30; the specific results are shown in Table 5.

Table 5: UserCF under different K-values

K	5	10	20	30
Recall	0.31121	0.33429	0.34957	0.34281
Precision	0.15481	0.16249	0.27543	0.16329
Popularity	3.09541	3.11428	3.13027	3.14438
Coverage	0.509128	0.51459	0.50129	0.49499

Through the experimental comparison, we can see that when K=5,10,20,30, the two tables change the same rule, that is, when K takes these four values, ItemCF and UserCF have the same properties. At the same time, when K=20, the system's Recall and Precision are higher, indicating that it is most appropriate to take the value of K. So the experiment shows that when K takes the appropriate value, the system's Recall and Precision are higher. So the experiments show that when K takes the appropriate value, the accuracy and coverage of the recommendations of the collaborative filtering recommendation algorithm based on music style classification are higher.

Recommended Results

The experiment generates recommendations by KNN algorithm and then calculates the scores of the recommended results by music genres, and selects the type of music style suitable for the user from the recommended results. In this study, the user with ID 803 is selected as an example, and the five users with the highest similarity to this user are found by calculating the five songs with the highest scores from the recommended 20 receipts, as shown in Table 6.

Table 6: Similar Users

User ID	Similarity
1026	0.61582
8426	0.61081
15687	0.60753
19230	0.59884
29321	0.59741

The recommended songs are shown in Table 7.

Table 7: Recommended song titles and artists

Song Title	Singer
Trouble I’m In	Twinbed
Gravity	Coldplay
One day	Emblem3
What Are Words	Chris Medina
I Like Me Better	Lauv

COMPARISON OF EXPERIMENTAL RESULTS

User-based Recommendations

This recommendation method is based on a collaborative filtering approach by calculating the similarities between users, using the user ID of 803 in the dataset as an example to recommend the top five songs in terms of similarity, as shown in Table 8.

Table 8: Recommended results based on users

Song ID	Similarity
142902542	0.327551
120213287	0.325473
308313843	0.319276
360062344	0.315423
531321323	0.308436

Music-based Recommendations

Music-based recommendations are mainly used to calculate the similarity between the songs listened to by the user and then to find songs that are more similar to future songs to recommend to the user. Similarly, using the word2vec model, the similarity is calculated by the number of likes of the songs in the song list ID of 110759778. Similarly, the top five songs with similarity are recommended, and the results are shown in Table 9.

Table 9: Recommended results based on music

Song ID	Similarity
115900031	0.319823
498708023	0.3176259
331398396	0.3152649
330634870	0.3091537
517438933	0.3056812

Time Migration-based Recommendations

Recommendations based on time migration mainly consider whether the user's music style changes after a period of time, by calculating the similarity of the user's music style at different times to make recommendations, this method is similar to the music-based recommendation method, but the range of songs considered is narrowed to the songs the user listens to.

Table 10: Recommended results based on time migration

Song ID	Similarity
692029375	0.3185233
533197318	0.3169182
256740225	0.3135139
109393127	0.3081456
379133594	0.3069437

From the above analysis, it can be seen that the similarity of recommendations from the three perspectives of user, music style and time migration alone is relatively low, while the accuracy of recommendations from the three perspectives jointly improves significantly.

CONCLUSION AND FUTURE WORK

Based on the collaborative filtering recommendation method, this study finds that the recommendation effect can be optimized by adjusting the K-value by using the KNN algorithm. In addition, this study finds that setting up a combined recommendation algorithm can optimize the recommendation system to some extent. Combined recommendations based on multiple perspectives, such as user attributes, style types and time migration, can well compensate for the shortcomings of other recommendation methods and thus improve the accuracy and coverage of online music recommendation systems. In the online music recommendation system, the style type scoring algorithm is used to calculate the higher score in the recommended songs, and the three perspectives of user attributes, music style and time migration are analyzed, and the recommendation system is constructed by combining these three perspectives. To a certain extent, the final recommendation result satisfies the user's music preferences, can better improve the accuracy of the recommendation system, and provide a reference for improving the algorithm design of the current online music recommendation system.

Through this research, it can be seen that the joint design based on user attributes, music style type and time transfer can more accurately recommend the music that users like, but this experiment also has some shortcomings. For example, the existing artificial intelligence such as deep learning has begun to be applied to the field of recommendation systems, and this research did not consider and test such technologies. This will also be a future development direction of online music recommendation systems, and future research can be explored in this direction.

REFERENCES

[1] Abbas, F., & Niu, X. (2019). One size does not fit all: Modeling users' personal curiosity in recommender systems. Retrieved from https://arxiv.org/abs/1907.00119 (December 1, 2020).

[2] Basu, Chumki, Hirsh, Haym & Cohen, William. (2000). Recommendation as classification: using social and content-based information in recommendation. Proceedings of AAAI-98.

[3] Bawden, D., Holtham, C., & Courtney, N. (1999). Perspectives on information overload. Aslib Proceedings, 51(8), 249-255.

[4] Celma, O. (2010). Music recommendation. In *Music recommendation and discovery* (pp. 43-85). Springer, Berlin, Heidelberg.

[5] Celma, Ò., & Serra, X. (2008). FOAFing the music: Bridging the semantic gap in music recommendation. *Journal of Web Semantics*, *6*(4), 250-256.

[6] Chen, L., Yang, Y., Wang, N., Yang, K., & Yuan, Q. (2019). How serendipity improves user satisfaction with recommendations? A large-scale user evaluation. In *The World Wide Web Conference* (pp. 240-250).

[7] Cheng, Y., & Bu, X. (2020). Research on key technologies of personalized education resource recommendation system based on big data environment. Journal of Physics: Conference Series, 1437(1), 012024 (9pp).

[8] Dazhi, X. U. (2020). Research on music culture personalized recommendation based on factor decomposition machine. Personal and Ubiquitous Computing, 24(2), 247-257.

[9] Deldjoo, Y., Elahi, M., Cremonesi, P., Garzotto, F., Piazzolla, P., & Quadrana, M. (2016). Content-based video recommendation system based on stylistic visual features. *Journal on Data Semantics*, *5*(2), 99-113.

[10] Gilda S, Zafar H, Soni C, et al. (2017). Smart music player integrating facial emotion recognition and music mood recommendation. International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET).

[11] Kaji, K., Hirata, K., & Nagao, K. (2005, November). A music recommendation system based on annotations about listeners' preferences and situations. In *First International Conference on Automated Production of Cross Media Content for Multi-Channel Distribution (AXMEDIS'05)* (pp. 4-pp). IEEE.

[12] Kautz, H., Selman, B., & Shah, M. (1997). Referral Web: combining social networks and collaborative filtering. *Communications of the ACM*, *40*(3), 63-65.

[13] Knees, P., Pampalk, E., & Widmer, G. (2004, October). Artist classification with web-based data. In Proceedings of 5th International Conference on Music Information Retrieval (ISMIR '04), pages 517-524, Barcelona, Spain, October 2004.

[14] Lee, Sangkeun. (2012). A generic graph-based multidimensional recommendation framework and its implementations. WWW'12 - Proceedings of the 21st Annual Conference on World Wide Web Companion.

[15] Logesh, R., & Subramaniyaswamy, V. (2019). Exploring hybrid recommender systems for personalized travel applications. In *Cognitive informatics and soft computing* (pp. 535-544). Springer, Singapore.

[16] Manogaran, G., Varatharajan, R., & Priyan, M. K. (2018). Hybrid recommendation system for heart disease diagnosis based on multiple kernel learning with adaptive neuro-fuzzy inference system. *Multimedia tools and applications*, *77*(4), 4379-4399.

[17] McNee, S. M., Riedl, J., & Konstan, J. A. (2006, April). Making recommendations better: an analytic model for human-recommender interaction. In *CHI'06 extended abstracts on Human factors in computing systems* (pp. 1103-1108).

[18] Pachet, F. (2005). Knowledge management and musical metadata. In Schwartz, D. (Ed.) *Encyclopedia of Knowledge Management*, Idea Group, 12.

[19] Patro, S. G. K., Mishra, B. K., Panda, S. K., Kumar, R., Long, H. V., Taniar, D., & Priyadarshini, I. (2020). A hybrid action-related k-nearest neighbour (HAR-KNN) approach for recommendation systems. *IEEE Access*, *8*, 90978-90991.

[20] Pazzani, M. J. (1999). A framework for collaborative, content-based and demographic filtering. *Artificial intelligence review*, *13*(5-6), 393-408.

[21] Resnick, P., & Varian, H. R. (1997). Recommender systems. *Communications of the ACM*, *40*(3), 56-58.

[22] Riyahi, M., & Sohrabi, M. K. (2020). Providing effective recommendations in discussion groups using a new hybrid recommender system based on implicit ratings and semantic similarity. *Electronic Commerce Research and Applications*, *40*, 100938.

[23] Schedl, M., & Hauger, D. (2012, April). Mining microblogs to infer music artist similarity and cultural listening patterns. In *Proceedings of the 21st International Conference on World Wide Web* (pp. 877-886).

[24] Shardanand, U., & Maes, P. (1995, May). Social information filtering: algorithms for automating "word of mouth". In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 210-217).

[25] Sharma, R. S., & Kale, R. (2018). Design of back-end of recommendation systems using collective intelligence social tagging. Paper presented at the 18th International Conference on Electronic Business, ICEB 2018, December 2, 2018 - December 6, 2018, Guangxi, China.

[26] Su, J. H., Chin, C. Y., Yang, H. C., Tseng, V. S., & Hsieh, S. Y. (2018, March). Music recommendation based on information of user profiles, music genres and user ratings. In *Asian Conference on Intelligent Information and Database Systems* (pp. 528-538). Springer, Cham.

[27] Wang, F., Wen, Y., Guo, T., Liu, J., & Cao, B. (2020). Collaborative filtering and association rule mining-based market basket recommendation on spark. *Concurrency and Computation: Practice and Experience*, *32*(7), e5565.

[28] Wang, Y., & Sharma, R. S. (2018). Design of front-end for recommendation systems: Towards a hybrid architecture. Paper presented at the 18th International Conference on Electronic Business, ICEB 2018, December 2-6, 2018, Guangxi, China.

[29] Xiang, L. (2012). Recommended system practice. *Posts and Telecom Press, Beijing*, 184-193.
[30] Yoshii, K., Goto, M., Komatani, K., Ogata, T., & Okuno, H. G. (2006, October). Hybrid collaborative and content-based music recommendation using probabilistic model with latent user preferences. In The 7th International Conference on Music Information Retrieval (ISMIR'06), Victoria, Canada, 8 - 12 October 2006.